

Data Streams: Bloom Filters

Mining Massive Datasets

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Sources

- Mining of Massive Datasets (2014) by Leskovec et al. (chapter 4)
 - Slides <u>part 1</u>, <u>part 2</u>
- Tutorial: Mining Massive Data Streams (2019) by Michael Hahsler

Bloom filters

Filtering a data stream

- Suppose we have a large set S of keys
- We want to filter a stream <key, data> to let pass only the elements for which key ∈ S
- Example: key is an e-mail address, we have a total of |S|=10⁹ allowed e-mail addresses

Hash tables

What's the Naïve solution?

Filtering a data stream

- . Suppose we have a large set S of keys
- We want to filter a stream <key, data> to let pass only the elements for which key ∈ S
- Example: key is an e-mail address, we have a total of |S|=10⁹ allowed e-mail addresses
- . Naïve solution? Hash table won't work, too big!
- use different hash tables
- Sol: move away from dict with all keys --> apply diff hash function --> check if keys are set to 1

Bloom Filter (1-bit case)

- . Given a set of keys S
- . Create a bit array B[] of n bits
 - Initialize to all 0s
- . Pick a hash function h with range [0,n)
 - For each member of s ∈ S
 - . Hash to one of *n* buckets
 - . Set that bit to 1, i.e., $B[h(s)] \leftarrow 1$
- For each element **a** of the stream
 - Output a if and only if B[h(a)] == 1

Bloom filter creation

Stream processing

Bloom Filter is an approximate filter

Can it output an element with a key not in S?

Can it not output an element with a key in S?

Bloom Filter is an approximate filter

- Can it output an element with a key not in S?
 - Yes, due to hash collisions h(x)=h(y) when $x\neq y$
- Can it not output an element with a key in S?
 - No, because h(x) is always the same for x

Bloom filters are permissive (not strict)

Bloom filter

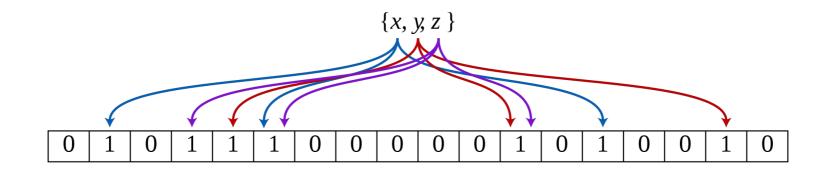
- . A bloom filter is:
 - An array of n bits, initialized as 0
 - A collection of hash functions h₁, h₂, ..., h_k
 Now >1 hash functions
 - A set S of m key values
- The purpose of the bloom filter is to allow all stream items whose key is in S

Bloom filter initialization

- . For all positions i in [0, n-1]
 - B[i] ← 0
- For all keys K in S:
 For every hash function h₁, h₂, ..., h_k
 B[h_i(K)] ← 1

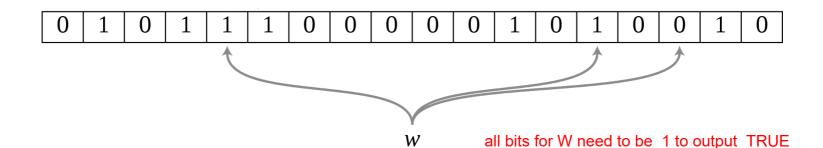
3 hash functions -> multiple elements might map to the same position of the bit array --> that is called COLLISION - it is important to find a balance

Check if all bits are 1



Bloom filter usage

For each input element <key, data> allow ← TRUE
 For every hash function h₁, h₂, ..., h_k allow ← allow ∧ B[h_i(K)] == 1 output element if allow == TRUE

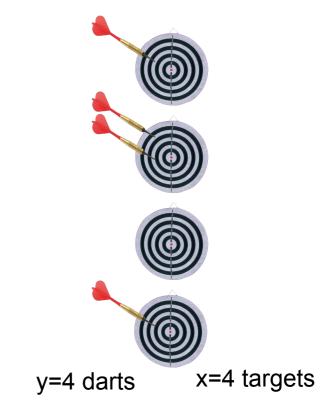


Characteristics of Bloom Filters

- . Are lax (not strict) and let some items pass
 - May require a second-level check to make filter strict, for instance store output on disk files and then check against hash tables (slower)
- . Implementations can be very fast
 - E.g., use hardware words for the bit table

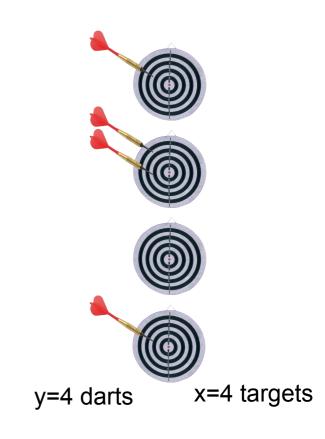
Preliminaries for the analysis: targets and darts

- Suppose we throw y darts at x targets
 - All darts will hit one of the targets



Preliminaries for the analysis: targets and darts (cont.)

- How many distinct targets can we expect to hit at least once?
 - Prob. that a given dart will hit a specific target is 1/x
 - Prob. that a given dart will **not** hit a specific target is
 1-1/x
 - Prob. none of the y darts will hit a specific target is $(1-1/x)^y = (1-1/x)^{x(y/x)}$
 - Using that $(1-\varepsilon)^{1/\varepsilon} \approx 1/e$ for small ε
 - If x is large, 1/x is small, and prob. that none of the y darts will hit a specific target is $(1/e)^{y/x}$



Analysis of the 1-bit Bloom Filter

- Each element of the signature S is a dart |S|=y
- Each bit in the array is a target n=x



- Suppose y=|S|=10⁹ (1 G) and x=n=8 x 10⁹ (8 G)
- Prob. that a given bit is **not** set to 1 (dart does not hit the target) is $(1/e)^{y/x} = (1/e)^{1/8}$
- Prob. that a given bit is set to 1 is $1 (1/e)^{1/8} = 0.1175$
- Expected number of bits that is set to 1 = 11.75% x 8GB
 - About 12% of bits are set to one in this Bloom Filter
 - this is also the false-hit probability in this case

General case

• |S|=m keys, array has n bits

Look at the previous slide Important to calculate false hit prob -> might be in exam

- k hash functions
- Targets x=n, darts y=km
- Probability that a bit remains 0 is $(1/e)^{km/n} = e^{-km/n}$
- False positive rate with k bits: (1 e^{-km/n})^k
 - This is the probability that all of the k bits are set to 1
- Example: we can pick k=n/m to obtain collision probability 1/e = 37%

Analysis of a 2-bit Bloom Filter

- Suppose $|S|=10^9 (1 G)$ and $n=8 \times 10^9 (8 GB)$
- Suppose we use two hash functions
- Prob. that a given bit is NOT set to 1 (dart does not hit the target) is $(1/e)^{y/x} = (1/e)^{1/4}$
- Prob. a bit is set to 1 is $1 (1/e)^{1/4}$
- Prob. two bits are set to 1 is $(1 (1/e)^{1/4})^2 = 0.0493$
- We have a false hit probability of about 5% with two hash functions, while the probability was about 12% with only one

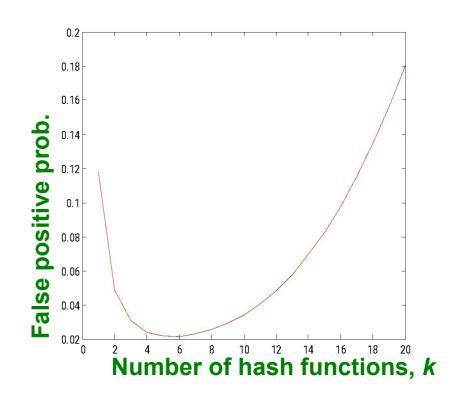
How many hash functions to use?

Too few: test is too unspecific. Too many: table becomes too crowded.

- m = 1 billion, n = 8 billion
 - False positive rate with k bits: (1 e^{-km/n})^k

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$$\mathbf{k} = \mathbf{1}$$
: $(1 - e^{-1/8})^1 = (1 - e^{-1/8}) = \mathbf{0.1175}$

- k = 2: $(1 e^{-2/8})^2 = (1 e^{-1/4})^2 = 0.0493$
- What happens as we keep increasing k?
 - "Optimal" value of k: n/m In(2)
 - In our case: Optimal k = 8 In(2) = 5.54 ≈
 - Error at k = 6: $(1 e^{-6/8})^6 = 0.0216$



Summary

Things to remember

- How to initialize a Bloom filter
- How to use a Bloom filter
- Proofs for 1-bit, 2-bit case

Exercises for TT22-T26

- Mining of Massive Datasets (2014) by Leskovec et al.
 - Exercises 4.2.5
 - Exercises 4.3.4
 - Exercises 4.4.5
 - Exercises 4.5.6